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An exploratory study of pilot EEG features during the climb and descent phases of flight

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Abstract

Objectives: The actions and decisions of pilots are directly related to aviation safety. Therefore, understanding the neurological and cognitive processes of pilots during flight is essential. This study aims to investigate the EEG signals of pilots to understand the characteristic changes during the climb and descent stages of flight.

Methods: By performing wavelet packet decomposition on the EEG signals, we examined EEG maps during these critical phases and analyzed changes in signal intensity. To delve deeper, we calculated the log-transformed power of electroencephalograms to investigate the EEG responses under different flight conditions. Additionally, we conducted EEG spectral coherence analysis to evaluate the degree of synchronization between different electrodes during climb and descent.

Results: This analysis helps us understand the functional connectivity changes in various brain regions during these phases. Understanding these complex interactions is crucial, as it provides insights into the cognitive processes of pilots during the critical climb and descent stages of flight, contributing to enhanced aviation safety.

Conclusions: By identifying how brain activity fluctuates during these phases, we can better comprehend pilots' decision-making processes, ultimately leading to the development of more effective training programs and safety protocols. This research underscores the importance of neurological studies in safety.

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Keywords: beta wave; climb and descent; spectral coherence; EEG map; log-transformed power

Introduction

According to data from the Aviation Safety Network on flight accidents, approximately 9 per cent of these accidents occur during the climb and descent phases of an aircraft, as illustrated in Figure 1 [1]. The frequency of accidents during these phases has led the research team to concentrate on studying pilots' flying behavior and EEG features [2]. Understanding these characteristics is crucial for reducing the incidence of accidents during the climb and descent phases of an aircraft, providing a theoretical foundation for accident prevention [3–5].

The climb and descent phases of flight are particularly challenging and require pilots to demonstrate exceptional skill and vigilance. During these phases, pilots must exhibit precise motor control in maneuvering the aircraft to a predetermined altitude accurately [6]. They must be proficient in various flight techniques, constantly making quick, well-informed decisions to ensure the aircraft's safe and efficient operation. This includes continuous monitoring of the aircraft's instruments, remaining alert to any changes in flight conditions, and being prepared to adjust their actions as necessary [7]. The dynamic nature of climb and descent requires pilots to integrate their technical knowledge with situational awareness. These are critical moments in any flight when expertise and experience play a crucial role.

At present, utilizing monitoring data to optimize pilot training methods has become an important development direction in the aviation industry. Through advanced sensing technology and data analysis tools, various physiological and psychological data of pilots during training can be collected and analyzed in real-time. These data include electrocardiography (ECG), electrooculogram (EOG), electroencephalogram (EEG), and flight control data [8].

Ting Pan et al. collected ECG data from pilots in simulated flight experiments through wearable wireless physiological devices, analyzed the variations in fatigue state indicators, and classified them using SVM [9]. Wright et al. examined the drowsiness and sleep exhibited by pilots based

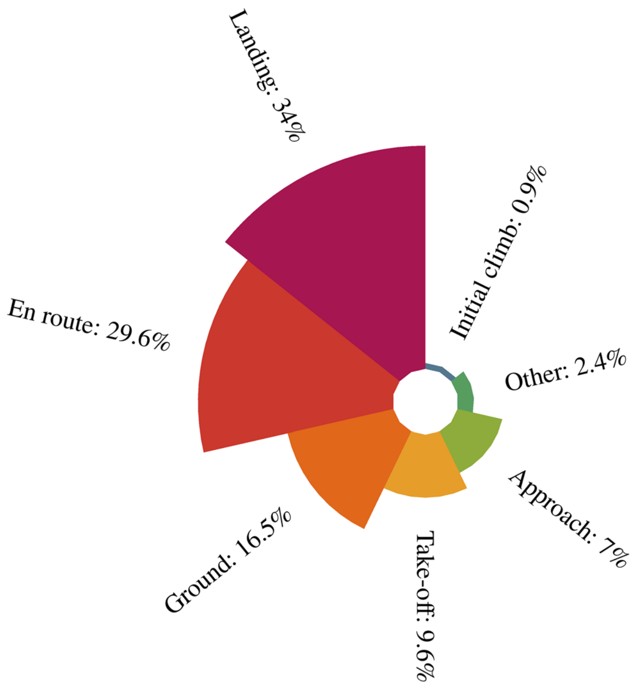

Figure 1: Percentage of fatal accidents.

on EEG and EOG data to prevent accidental sleep during flight and ensure that pilots who do not nap stay awake [10].

Compared to ECG and EOG, EEG records electrical signals from neuronal activity in the brain, directly reflecting the state and function of the brain [11]. This is crucial for understanding pilots' cognitive load, emotional state, and attention level in different contexts. In addition, EEG signals contain various frequency bands, such as alpha, beta, theta, and delta waves, each associated with different brain functions. For example, alpha waves are typically associated with relaxed states, while beta waves are linked to focused attention and heightened alertness. By analyzing these frequency components, a comprehensive understanding of the pilot's brain function can be obtained [12]. Klaproth et al. developed a classifier capable of recognizing the neurophysiological responses of pilots to cockpit alarms and messages. Through this neural adaptive technology, the pilot's perception and processing of cockpit alarms can be measured and tracked [13]. Li et al. examined the components of four typical EEGs during emergency collision avoidance to analyze the potential patterns of different EEG components and identify EEG activity patterns during collision avoidance [14]. Binias et al. explored the correlation between brain wave activity and reaction time in short-haul pilots using EEG data [15]. Additionally, Zhang et al. examined the brain attributes related to pilots' error awareness during flight missions using EEG in their study [16].

In previous studies, we analyzed the EEG characteristics of pilots during takeoff and landing phases and their focus state using logistic regression [17]. Therefore, this study examines EEG responses during the ascent and descent phases. This study identifies three specific research objectives and their corresponding hypotheses:

- This study examines the differences in EEG maps responses during the ascending and descending phases of the entire flight mission. Additionally, the differences in EEG maps of four different bands (delta, theta, alpha, and beta) are analyzed.
- This study investigates the patterns of different EEG wave segments (delta, theta, alpha, and beta) during the ascending and descending processes. It is hypothesized that as flight missions progress, some EEG bands will show significant changes.
- This study analyzed the spectral coherence of the pilot's EEG during the ascending and descending stages to understand the information transmission in the pilot's brain and the connectivity of EEG signals between different brain regions.

Materials and methods

Participants

The participants in this study consisted of 15 professional pilots, all of whom had prior experience with flight simulation experiments. To ensure a standardized and reliable dataset, participants were required to fulfill the following criteria:

- At least 50 Hours of Flight Simulation Experience: Each participant was required to have at least 50 h of experience with flight simulations to ensure they were sufficiently familiar with the procedures and controls used in the experiment.
- Right-Handedness: This criterion was established to minimize variability in motor control and coordination, as the majority of standard aviation controls are designed for right-handed individuals.
- Absence of Unhealthy Habits: Participants were required to abstain from unhealthy habits such as smoking and drinking, which can affect cognitive and physical performance.
- Height Requirement: Participants were required to have a height of 175 ± 2 cm to ensure uniformity in how they interacted with the flight simulation setup, as variations in height could affect reach and comfort with the equipment.

- Age Requirement: Participants were required to be 24 ± 2 years old to maintain a consistent age range, which helped in controlling for age-related variations in cognitive and physical abilities.
- No prior EEG experiment participation: Participants should not have prior involvement in EEG experiments to prevent any potential residual effects on the EEG data, thus ensuring the independence and validity of the results.

Each participant was scheduled to perform a flight simulation experiment. The day before the experiment, participants were briefed on the procedures and assured that the data acquisition equipment would not interfere with the flight simulation experience. This acclimation process included acquainting them with the experimental equipment to ensure they were comfortable and confident during the actual test. Additionally, they were advised to maintain a balanced diet and ensure adequate sleep the night before the experiment, ensuring they were in optimal physical and mental condition [18].

The experiments in this study were conducted in a controlled laboratory environment. The ambient temperature was controlled at 25 °C (±1 °C) to ensure consistency across all trials. Humidity levels were maintained within a range of 45–55 %. Lighting and noise levels were minimized to reduce potential external influences on the participants.

On the day of the experiment, participants voluntarily signed an Informed Consent Form while fully awake and aware of the study's details. To ensure they were adequately hydrated and had sufficient energy, they were allowed to drink a small amount of water before starting the experiment. Upon completion of the flight simulation experiment, participants received compensation in accordance with the terms outlined in the consent form.

This rigorous preparation and strict adherence to participant criteria were essential in ensuring the experiment was conducted under optimal and standardized conditions, thus enhancing the accuracy and reliability of the collected data.

Experimental equipment

Emotiv EPOC+ EEG cap

The Emotiv EPOC+ EEG cap is capable of recording 14 channels of EEG data, providing comprehensive coverage of all brain regions. The cap is equipped with semi-dry electrodes, which enhance participant comfort while ensuring high-quality signal acquisition. Moreover, the cap's ability to transmit data wirelessly reduces movement restrictions on pilots, making it ideal for dynamic and realistic simulation environments [19].

KDKJ-FX-172-6D flight simulator

The KDKJ-FX-172-6D flight simulator is a versatile and sophisticated tool capable of being tailored to the specific needs of the experiment. It enables the design of customized flight simulation environments and can accurately replicate real flight scenes. This high level of customization and realism ensures that the experimental conditions closely mimic actual flight situations, thus providing valuable data for the study [20].

Experimental scheme

The present study employed simulated flight experiments, illustrating their feasibility and effectiveness as credible alternatives to actual flight scenarios. Consequently, each pilot performed a trial in a flight simulator. During this trial, pilots had to complete the take-off, climb, descent, and landing phases of the flight. Each phase needed to be separated by a minimum time interval of 10 s to ensure a clear transition and sufficient data collection [21].

- Take-off phase: During this phase, the aircraft flies at a speed of 60 knots while reaching an altitude of 400 feet.
- Climb phase: In this phase, the aircraft ascends at a rate of 15 feet per second while maintaining a constant flight speed.
- Descent phase: In this phase, the aircraft descends at a rate of 15 feet per second while maintaining a constant flight speed.
- Landing phase: The aircraft gradually reduces both speed and altitude to accomplish a smooth landing, focusing on the precision and control required to complete the landing successfully.

Throughout the entire flight, the pilot operates under Visual Flight Rules (VFR), a flight method that relies on visual reference and pilot judgment. VFR flights are primarily conducted in good weather and high visibility conditions. Pilots must possess strong visual navigation skills and consistently observe and monitor the surrounding environment [22].

EEG pre-processing

The EEG signals were preprocessed using the EEGLAB software in MATLAB, focusing on removing power frequency interference, noise, and eye-electric artifacts. Here's a detailed outline of the specific preprocessing steps:

Electrode impendences

To ensure optimal data quality, this study maintained the electrode impedance within the range of 10–15 kΩ. This approach ensures signal stability and accuracy while minimizing noise and artifacts resulting from impedance mismatch.

Reference and grounding electrodes

The P7 and P8 electrodes are designated as reference electrodes, while the P3 electrode is designated as the grounding electrode.

The number of bad channels and number of bad epochs

During data preprocessing, we assessed all electrodes and analyzed the recorded time periods. The results indicated that the signal quality of all electrodes was satisfactory, with no defective electrodes identified. No problematic periods were detected in the data. These results ensure the integrity and reliability of the data, establishing a robust foundation for subsequent analysis.

Notch filter

A notch filter was initially applied to remove 50 Hz power frequency interference from the original EEG signals. This step is crucial as power line interference can distort the EEG signals, affecting the accuracy of subsequent analysis.

Bandpass filtering

Following the notch filtering, the EEG signals were then filtered using a bandpass filter with a frequency range of 0.5–40 Hz. This bandpass filtering helps to isolate the frequency bands of interest for EEG analysis while further reducing noise from other frequencies [23, 24].

Independent component analysis (ICA)

Independent Component Analysis (ICA) was employed to specifically address and remove artifacts related to eye movements and blinks, known as eye-electric artifacts. ICA separates the EEG signals into independent components, enabling the identification and exclusion of components associated with artifacts while preserving components related to brain activity [25, 26].

Results

EEG map during the climb and descent stages

The EEG data for each pilot were extracted 1 s before and 2 s after the task behaviours (climb and descent phases). The data were then averaged and superimposed to enhance the signal-to-noise ratio. The intensity of the EEG signals across different brain regions was visualized using an EEG map (absolute voltage values), to comprehend the activity levels of the EEG signals across different regions of the scalp surface during various task behaviours.

Prior to the aircraft's climb, the intensity of EEG signals across all electrode channels on the pilot's EEG map was low, with microvolt values indicating minimal brain activity. During the climb phase, the color intensity in the AF3, AF4, F3, and F4 electrode channels (frontal lobe) deepened, indicating an increase in EEG signal intensity, measured in microvolts. This observation aids in understanding the changes in brain activity during the climb phase. Upon completion of the climb, the EEG signal intensity across all electrode channels decreased, reverting to pre-climb levels, as illustrated in Figure 2A. Moreover, changes in other brain regions were relatively minor compared to those in the frontal lobe.

Prior to landing, the EEG signal intensity across all electrode channels on the pilot's EEG map was lower, with microvolt values reflecting diminished brain activity. During the descent phase, the EEG signal intensity in the AF3, AF4, F3, and F4 electrode channels (frontal lobe) increased, with higher microvolt values indicating enhanced brain activity and a more engaged state in the pilot's brain. Upon completion of the descent, the EEG signal intensity decreased, with microvolt values returning to levels comparable to those observed prior to the descent, as depicted in Figure 2B. Moreover, changes in other brain regions were relatively subtle in comparison to the frontal lobe.

As shown in Figure 3, the pilot's climb and descent processes are segmented into five stages: low-altitude cruising (Stage 1), climb (Stage 2), high-altitude cruising (Stage 3), descent (Stage 4), and final low-altitude cruising (Stage 5).

Figure 4 illustrates the EEG maps of four frequency bands at different stages [12]. The colors in the maps (ranging from green to deep red) indicate the level of EEG activation. The greener the color, the lower the activity; the redder the color, the higher the activity. Intuitively, the EEG maps of delta waves and beta waves display larger red regions (frontal lobe) during the climb and descent stages compared to the cruising stage, indicating that the pilot's

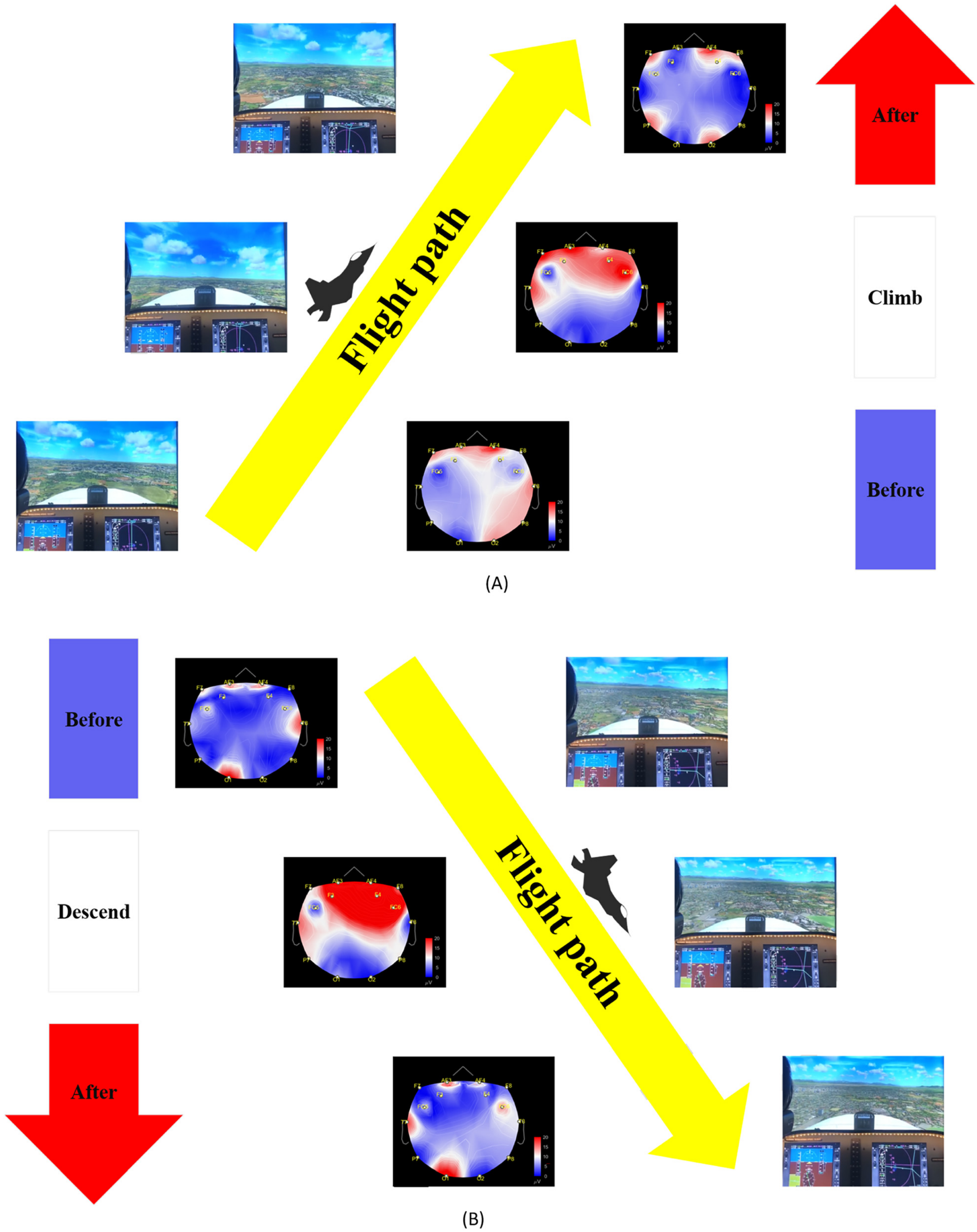

Figure 2: EEG map during two distinct stages. (A) EEG map during the climb stage; (B) EEG map during the descent stage (The colorbar represents the absolute values of the EEG signals).

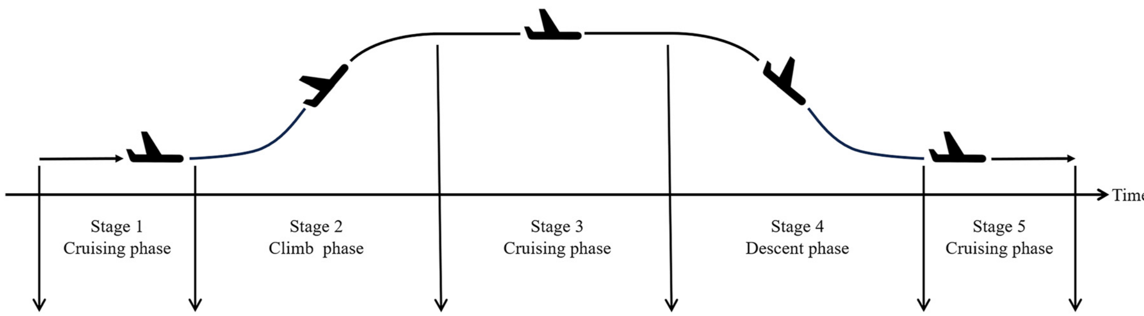

Figure 3: The five-stage process.

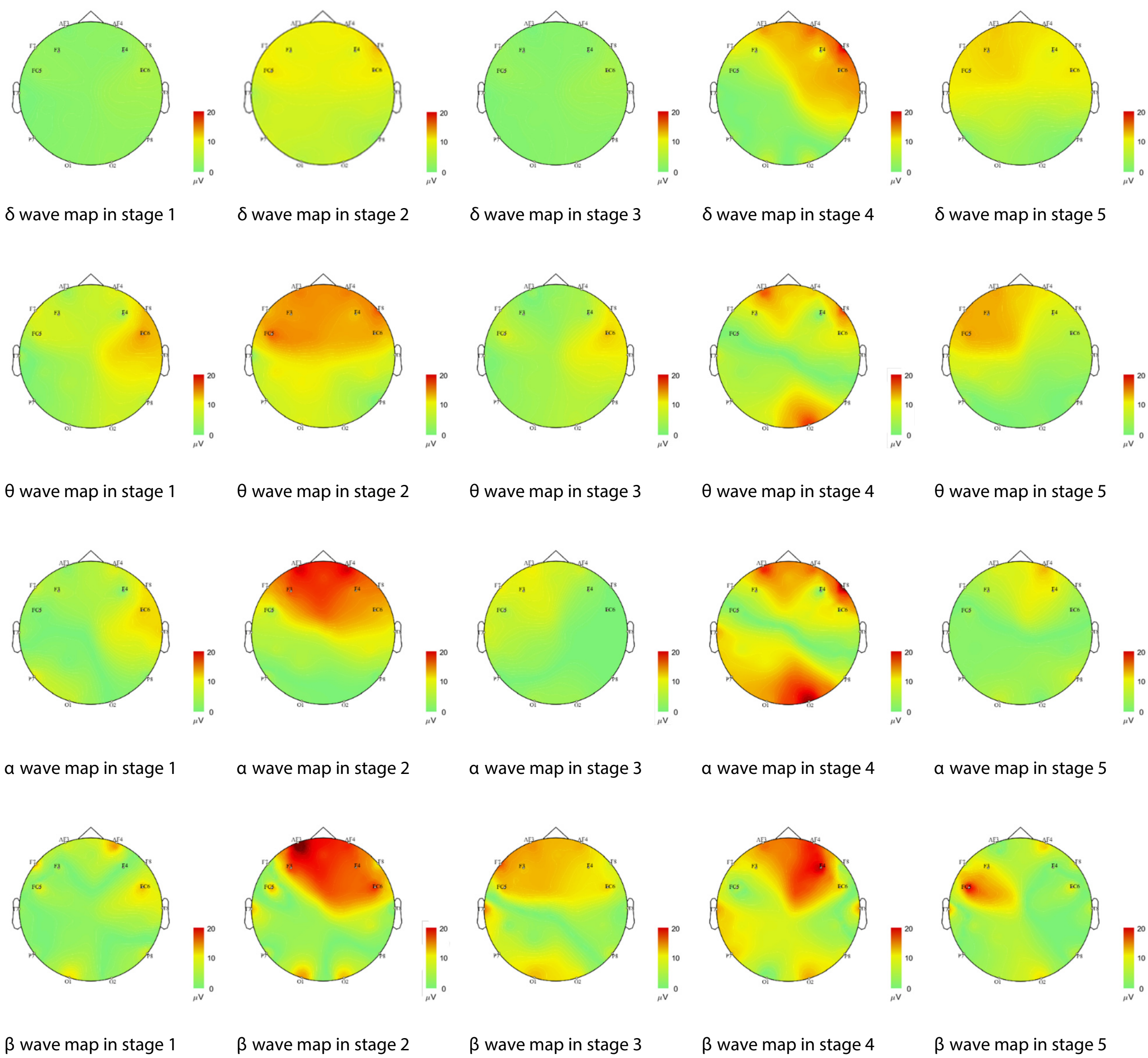

Figure 4: EEG maps of the four waves at different stages for the pilot (The colorbar represents the absolute values of the EEG signals).

mental state is more stable during the cruising stage compared to the climb and descent stages. Notably, the depth of the colors in the maps reflects the visualized EEG activity, directly reflecting the EEG activity of the pilot at different stages [27].

Log-transformed power of EEG

The log-transformed power (LTP) of EEG is extensively employed for processing EEG data. Given the high dynamic range and complex spectral characteristics inherent in EEG signals, LTP is particularly suitable for handling data with large range spans or skewed distributions. The application of log transformation aligns the data closer to a normal distribution, thereby facilitating various statistical analyses [28].

For each stage, the Fast Fourier Transform (FFT) was applied to convert the EEG data from the time domain to the frequency domain. From the frequency domain data, the log-transformed power (LTP) of the four EEG frequency bands (δ (0.5–3 Hz), θ (4–7 Hz), α (8–13 Hz), and β (14–30 Hz) bands) were then calculated [29].

Table 1 provides the descriptive statistics for the log-transformed power of the four EEG frequency bands – delta, theta, alpha, and beta – across the five experimental stages. The table details the mean and standard deviation for each frequency band at each stage. To determine whether the power of these frequency bands varies significantly across the stages, a repeated measures ANOVA was performed. The analysis identified significant changes in the log-transformed power (LTP) of the delta, alpha, and beta bands, indicating that these frequency bands exhibit distinct variations in response to the experimental conditions [30].

Post-hoc test results, as illustrated in Figure 5 (with error bars representing standard deviation), demonstrate that the LTP of theta, alpha, and beta waves during the climb stage (Stage 2) and descent stage (Stage 4) was significantly higher compared to the normal cruising stages (Stage 1, Stage 3, and Stage 5). Additionally, the LTP of beta and delta waves was significantly higher than that of alpha and theta waves across all stages.

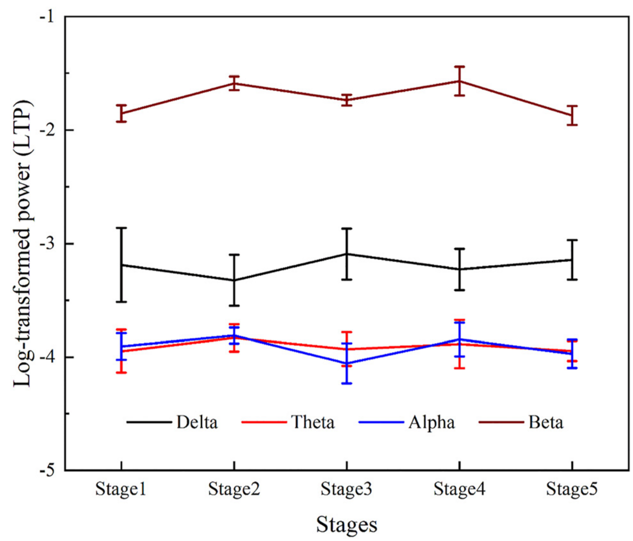

Figure 5: The change of LTP of four EEG bands in five stages.

Power ratio of EEG

The EEG power ratio is a crucial method for analyzing EEG signals. It is frequently employed to investigate relative changes in brain activity across various frequency bands, thereby elucidating the functional state of the brain. Figure 6 (which includes error bars that represent the standard deviation) depicts both the average and standard deviation of the power ratio (PR) for four EEG frequency bands across 15 participants at different stages [31, 32].

Figure 6 illustrates the power ratios of various EEG frequency bands during different stages of flight. Specifically, the data indicate that during stages 2 and 4 (the climbing and descending phases), there is a notable increase in the alpha power ratio and beta power ratio and a decrease in the delta power ratio. Furthermore, the changes in the theta power ratio during these stages remain relatively small.

Table 1: Descriptive statistics and repeated-measures ANOVA results of EEG band LTP in five stages.

EEG band	Variables	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	*n*	*df*	*F*	p-Value	η_p^2
Delta	LTP	−3.19 (0.33)	−3.32 (0.23)	−3.09 (0.23)	−3.23 (0.18)	−3.14 (0.17)	15	4	8.413	<0.001	0.425
Theta	LTP	−3.95 (0.19)	−3.83 (0.12)	−3.93 (0.15)	−3.89 (0.21)	−3.95 (0.09)	15	4	1.008	0.413	0.094
Alpha	LTP	−3.91 (0.12)	−3.81 (0.07)	−4.06 (0.18)	−3.85 (0.15)	−3.97 (0.12)	15	4	5.953	<0.001	0.398
Beta	LTP	−1.85 (0.07)	−1.59 (0.06)	−1.73 (0.05)	−1.57 (0.13)	−1.87 (0.08)	15	4	27.916	<0.001	0.756

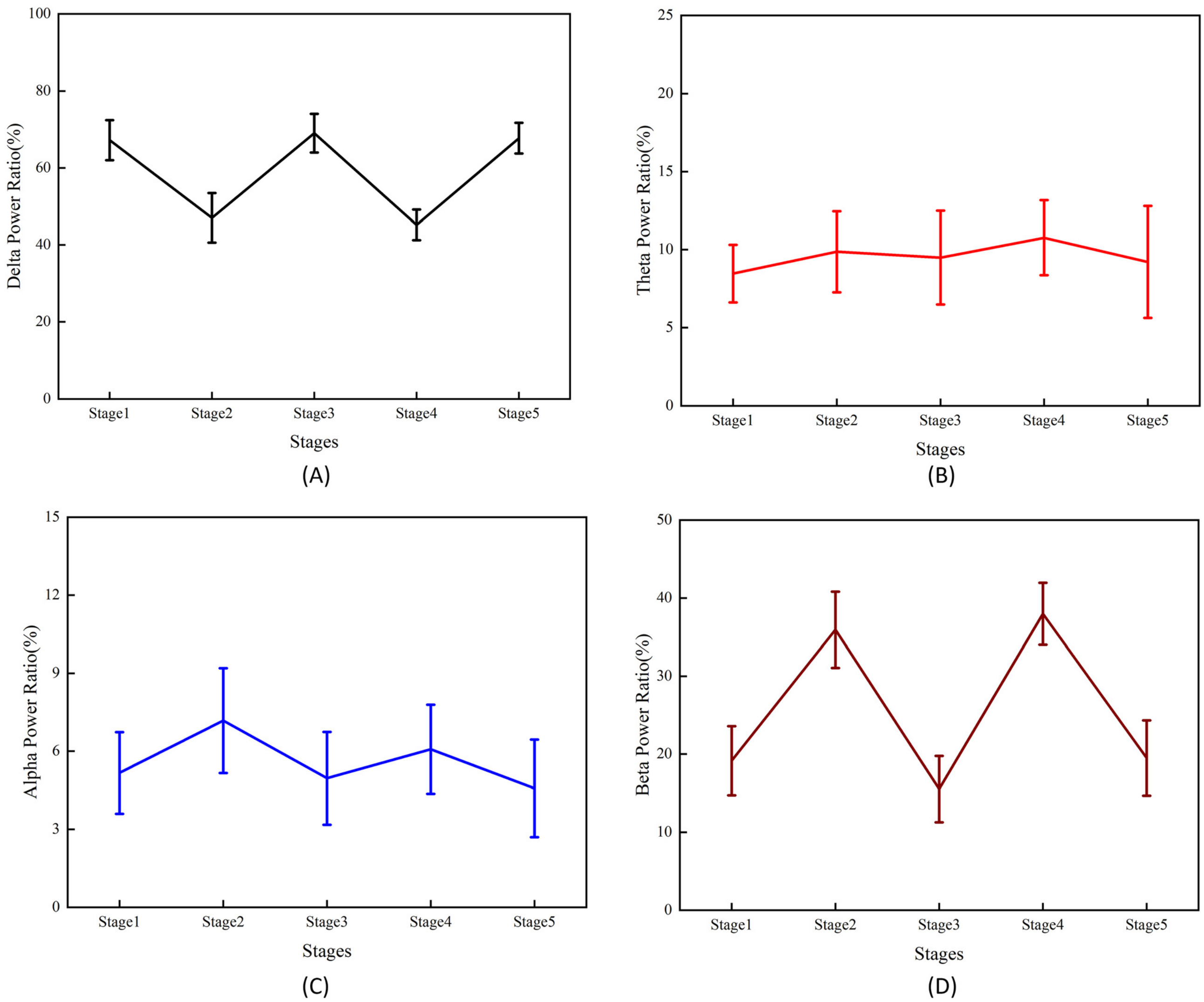

Figure 6: EEG band power ratio in different flight stages. (A) Delta power ratio; (B) theta power ratio; (C) alpha power ratio; (D) beta power ratio.

Spectral coherence of EEG

Spectral coherence (Coh) of EEG is defined as the synchronization or correlation of EEG activity between different brain regions at a specific frequency. It is a quantitative indicator describing the degree of connectivity of EEG signals between different brain regions. The spectral coherence of EEG spectra is measured by calculating the phase and amplitude relationship between different brain regions within a specific frequency range to assess their synchronization. Simply put, spectral coherence quantifies the degree of resonance of signals between different brain regions [33].

The analysis of EEG spectrum coherence is extremely valuable for studying information transmission, functional networks, and interaction relationships between brain regions. Initially, in this study, EEG signals were selected from the climb and descent stages, and the Fourier transform was employed to convert these time-domain signals into frequency-domain signals. We calculate the cross-spectrum between the two electrode signals using the following equation:

$$S_{xy}(f) = X(f)Y^{*}(f), \tag{1}$$

where $S_{xy}(f)$ denotes the cross-spectrum between different signals. $X(f)$ and $Y(f)$ denote the Fourier transforms of the two signals at frequency f, and * denotes the complex conjugate operation. Finally, the ratio of the cross-spectrum to the self-spectrum is calculated as:

$$C_{xy}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f) \cdot S_{yy}(f)}, \tag{2}$$

where $C_{xy}(f)$ denotes the spectral coherence estimate of the two signals at the frequency f, and $S_{xy}(f)$ is the cross spectrum between the two signals. $S_{xx}(f)$ and $S_{yy}(f)$ denote the respective autospectra of the two signals. Considering the differences in brainwave spectral coherence among different pilots and enhancing the spectral coherence contrast, the spectral coherence of pilots during climb and descent phases is normalized [34]. The normalized function is defined by:

$$X_{\mathrm{n}} = \frac{X - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}}, \tag{3}$$

where X indicates the original characteristic parameter. X_{n} is the normalized value of X. X_{min} is the minimum value of X in the dataset. X_{max} is the maximum value of X in the dataset. The spectral coherence results at different stages are depicted in Figure 7.

Figure 7 illustrates the spectral coherence between various electrodes in the cerebral cortex of pilots during the climb and descent phases. Figure 7A depicts the spectral

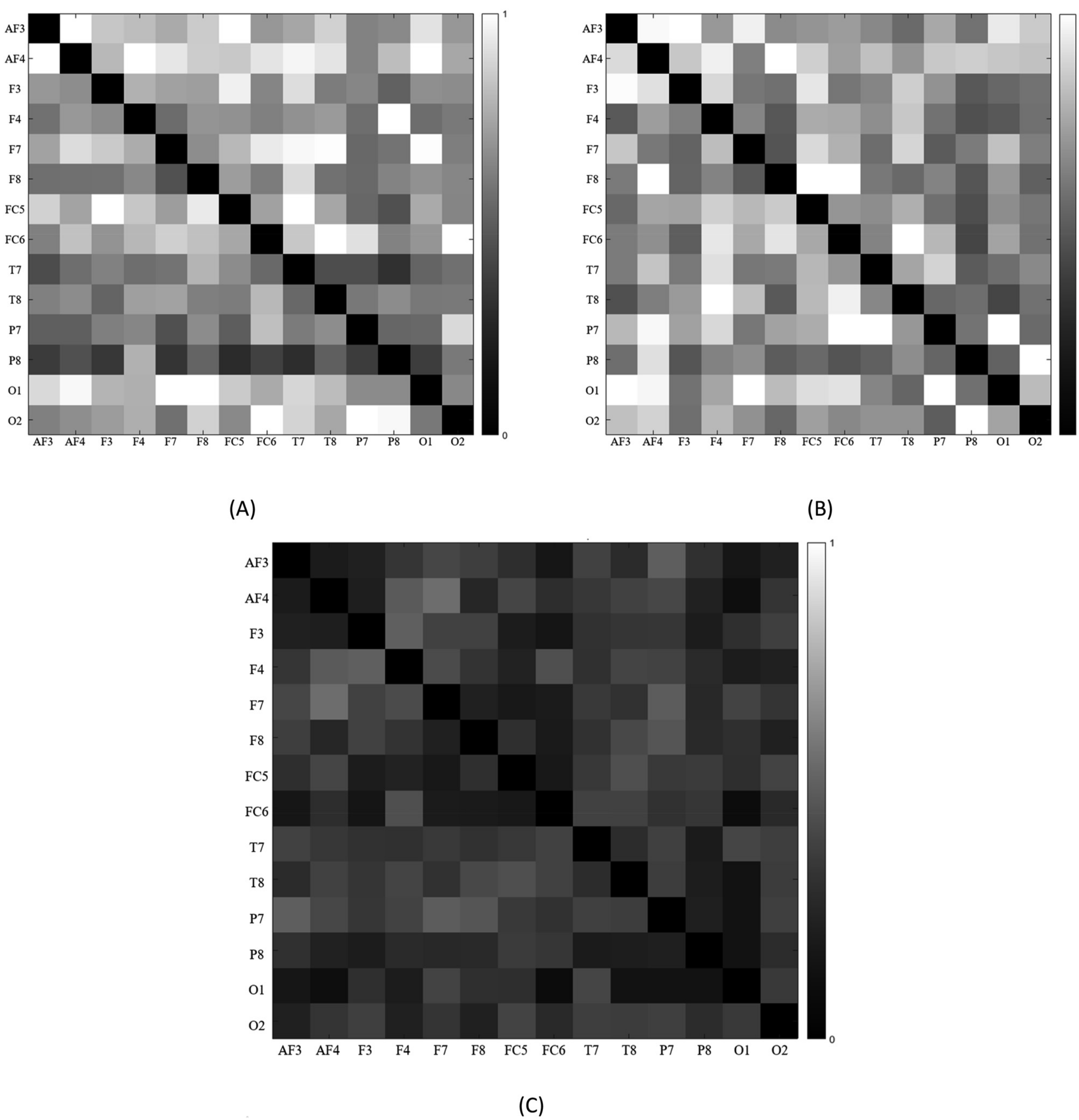

Figure 7: Spectral coherence analysis of electrodes in the brain. (A) Spectral coherence in the climbing phase; (B) spectral coherence in the descending phase; (C) spectral coherence in the cruise phase.

coherence during the climb phase, whereas Figure 7B depicts the coherence during the descent phase.

Figure 7 provides an analysis of the spectral coherence between electrode pairs (AF3-AF4, F3-F4, F7-F8, O1-O2, FC5-FC6, P7-P8, and T7-T8) in the bilateral cerebral cortex regions during the climb and descent phases. During both the climb and descent phases, the spectral coherence between AF3-AF4 electrode pairs is notably high, whereas that between P7-P8 electrode pairs is relatively low. Furthermore, the differences in spectral coherence between the same electrode pairs across the different phases are minimal and statistically insignificant.

Moreover, Figure 7 offers further insights into the relationships among different brain regions. Within the same brain regions, during both the climbing and descending phases, the frontal lobe demonstrates higher coherence values, suggesting stronger functional connectivity within this region. Coherence between the frontal and occipital lobes is the highest among all brain region pairings. Overall, the data suggest that the climb and descent phases of flight impact brain activity, particularly the connectivity between the frontal lobe and other brain regions. These findings enhance our understanding of pilots' brain activity during both climb and descent phases.

Figure 7C illustrates the EEG coherence of pilots during the cruise phase. Compared to the ascent and descent phases, EEG coherence during the cruise phase is lower. This suggests that the synchronous activity between different brain regions decreases during cruising, possibly due to lower operational demands.

Discussion

This study aims to investigate the relationship between pilot control behavior and EEG data during the climb and descent phases of flight. First, we observed the changes in brainwave signal intensity during different flight stages using electroencephalography (EEG), and analyzed the performance of four different EEG rhythms during these stages. The research results show that during the climb and descent phases of flight, the changes in the pilot's EEG data in the frontal lobe region are particularly significant. Notably, we observed that the EEG changes in the beta wave rhythm were most significant during the pilot's climb or descent operations. This finding is consistent with the results of Lin et al., who found that beta waves in the frontal lobe are associated with cognitive processes, such as judgment, working memory, and decision-making [35].

According to previous research, Kiymik et al. found that when a person is in an alert state, beta waves in the brain exhibit faster fluctuations in activity [36]; Borghini et al. found that the presence of delta waves is largely associated with mental fatigue [28]; Sonnleitner et al. found that changes in alpha wave activity in EEG are related to tasks requiring attention [37–39]. The current results are consistent with our recent research, where we calculated the log-transformed power of various rhythms and employed repeated-measures ANOVA. We observed significant variations in delta, alpha, and beta waves across different stages, with theta waves showing comparatively minor changes. Additionally, the power ratio calculations for these rhythms revealed significant differences in EEG activity between delta, alpha, and beta waves during the climb and descent phases.

And through spectral coherence analysis, we aim to understand the connectivity of different brain regions in pilots during various task behaviors. Our research is of great significance to the aviation industry. By understanding the EEG characteristics related to critical flight stages, we can develop more effective training plans tailored to these needs, thereby assisting pilots in managing cognitive load and maintaining high performance levels during climb and descent, ultimately contributing to improved aviation safety.

Conclusions

This exploratory study provides valuable insights into EEG features of pilots during the climb and descent phases of flight. By examining the EEG signals and their log-transformed power, we identified distinct changes in brain activity and functional connectivity that underscore the heightened cognitive and motor demands placed on pilots during these critical flight stages.

Our results revealed that during the climb and descent phases, there is a significant increase in brain activity in the frontal lobe regions, as indicated by the EEG maps and log-transformed power (LTP) analysis. The elevated beta wave activity reflects pilots' increased focused attention. Additionally, the spectral coherence analysis demonstrated enhanced synchronization between different brain regions, thereby supporting efficient information processing and coordination necessary for managing the dynamic flight environment.

These findings have important implications for the aviation industry. Understanding neurological and cognitive processes of pilots during the climb and descent phases can inform the development of more effective training programs tailored to these specific demands. Enhanced training can help pilots manage cognitive load, maintain high performance levels, and improve overall flight safety. Furthermore, our research can guide the design of cockpit interfaces and support systems that optimize pilots' cognitive workload and situational awareness.

Future research should continue to explore neurological and cognitive aspects of flight, incorporating a broader range of flight phases and conditions to provide a more comprehensive understanding of pilot performance. By deepening our understanding of pilots' cognitive and neurological responses, we can contribute to the advancement of aviation safety and the development of technologies that support pilot performance.

Future work

In future research, we plan to further explore the specific effects of different aircraft ascent and descent rates on pilot EEG characteristics. We simultaneously aim to account for other influencing factors, such as pilot gender and changes in light intensity during flight, to comprehensively analyze the potential effects of these variables on EEG characteristics. Our objective is to accurately uncover the psychological and physiological response mechanisms of pilots in complex flight environments by introducing these variables.

Research ethics: The local Institutional Review Board deemed the study exempt from review.
Informed consent: Not applicable.
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Use of Large Language Models, AI and Machine Learning Tools: None declared.
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Data availability: The raw data can be obtained on request from the corresponding author.

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